Estimating Recharge Uncertainty using Bayesian Model Averaging and Expert Elicitation with Social Implications

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AUTHORIZATION TO SUBMIT

THESIS

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Abstract

Expert elicitation is used in concert with Bayesian Model Averaging (BMA) to estimate recharge and an associated uncertainty to the Wanapum aquifer in the Moscow, Idaho area. Twelve studies that utilize eight distinct methods to estimate recharge are used in an expert elicitation process designed to address four issues: the completeness of the set of methods used in the studies to determine recharge to the Wanapum aquifer; the plausibility ranks of each of the studies; the probability value representing the experts confidence in each of the studies; and the variance of each of the studies. Experts from the University of Idaho, Washington State University, the Palouse Basin Aquifer Committee, and a private consulting firm participated in the elicitation process. The quantities elicited are the prior probabilities and the variance for the twelve studies. These are used as input into the BMA scheme to obtain a recharge estimate of 2.0 ± 1.8 inches per year.

Reasonable consistency between expert judgments is observed, and thus the BMA-derived annual recharge depth is expected to represent a best current depth-based estimate, with quantitative uncertainty bounds potentially useful in decision making. The experts indicated that better estimates could be given if more time and resources were available to devote to elicitation. Experts expressed concern about the scale and applicability to recharge of some studies, and indicated that the more simple studies that focused specifically on the Wanapum aquifer likely gave the best results. The set of methods is not complete; additional tracer work is recommended.

Recharge to the Wanapum aquifer remains uncertain. Uncertainty should not prevent decision making, but provides a basis for choosing between various alternatives, particularly

when quantitative values can be clearly communicated. To place the BMA recharge estimate in a decision making context, the broad effects of physical and social uncertainty on the decision making process are assessed in collaboration with a social scientist. Decision makers have an incentive to adopt the Precautionary Principle without physical and social certainty guiding decisions. The BMA estimate can quantitatively inform decision makers in developing management plans consistent with this principle, and can be updated as new recharge estimates are made. The overarching management strategy best equipped to deal with uncertainty appears to be some form of adaptive management which involves scientists, managers, decision-makers, and the public.

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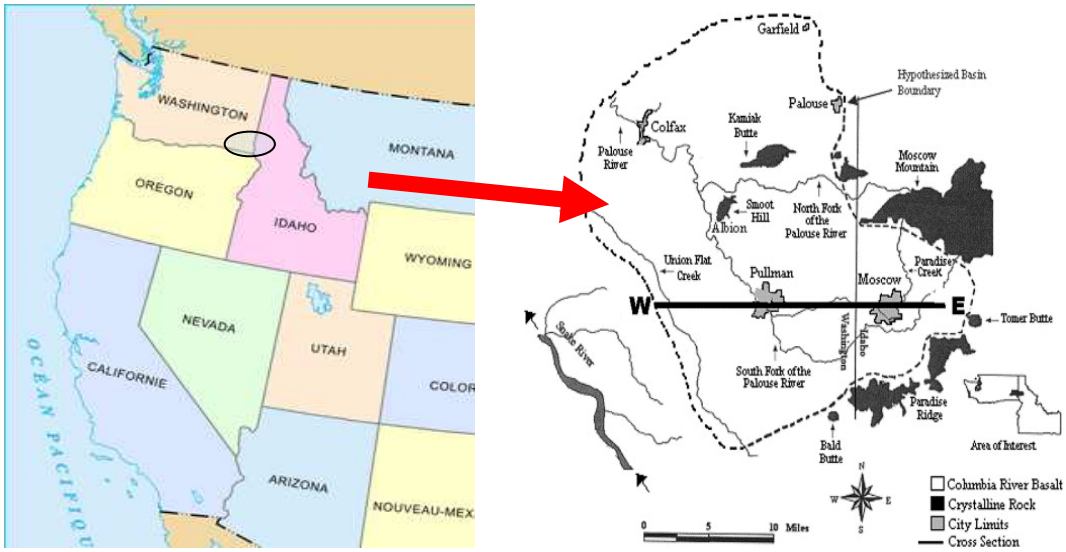
Chapter I

Palouse Basin Overview

1.0 Introduction

The Palouse Basin is home to the cities of Moscow, Idaho and Pullman, Washington and covers approximately 235 square miles (Douglas, 2007) in eastern Washington and northwestern Idaho. Several smaller towns such as Colfax, Albion, and Palouse in Washington, and Potlatch and Viola in Idaho as well as rural residents make up the rest of the population of the basin(approximately 52,000; Community Water Information System). The University of Idaho is located in Moscow, Idaho, and eight miles to the west is Washington State University in Pullman, Washington. The location of the Palouse Basin is shown in figure 1.



(wikimedia.org, 1 Sept. 2008) (Douglas et al, 2007)

Figure 1: Location of Palouse Basin

Moscow, ID and Pullman, WA have been the major groundwater users in the Palouse Basin since the first wells were drilled in the late 1800s. According to I. C. Russell (1897) the first artesian well was the M. C. True well drilled in Pullman, WA in 1894. It supplied 30,000 gallons per day and had sufficient pressure to cause water to rise in a pipe 20 feet above the ground surface. Eleven wells that were completed in the flood plain of the South Fork of the Palouse River by 1896 were flowing artesian wells. In the Moscow, ID area, 14 wells had been drilled since 1890 and 10 of those were flowing artesian wells in 1891, but by 1896 water levels had dropped to 8 to 9 feet below land surface. Russell had the foresight to see that the supply of water was not unlimited and made this observation.

> *"Several of the wells at Pullman are allowed to flow, thus wasting a large volume of water and decreasing the pressure. If the blessings accompanying the discovery of an excellent water supply are to be maintained, all wells should be closed when not in use" (Russell, 1897).*

Water use in Pullman and Moscow increased as more development in the basin occurred. The groundwater used by both cities is drawn from a sole source aquifer system with an upper and a lower aquifer known as the Wanapum aquifer and Grande Ronde aquifer, respectively. Water level declines have become an increasing problem since the development of the resource in the late 1800's.

1.1 Geologic Setting

This is a brief summary of the basin geology intended to provide a general understanding only; for in-depth geological descriptions, see Foxworthy and Washburn (1963), Barker (1979) and Bush (2005). The Palouse Basin is underlain by Miocene Era basalt and sediments which lie on pre-Tertiary crystalline basement rock. The basin is capped by Pleistocene loess which ranges from a few feet to several hundred feet thick (Lum

et al, 1990). The Miocene basalt belongs to the Columbia River Basalt Group (CRBG). The Wanapum and Grande Ronde aquifers are contained in the Wanapum and Grande Ronde basalts and sediments of the Latah Formation can be found interbedded, underlying, and overlying the basalts (Bush, 2005).

The upper Wanapum aquifer system consists of basalts from the Priest Rapids Member of the Wanapum Formation, sedimentary interbeds of the Latah Formation and the underlying sediments of the Vantage Formation. The Wanapum aquifer is tapped by the City of Moscow and rural homeowners with private wells. The lower Grande Ronde aquifer is housed in the Grande Ronde Formation and is separated from the Wanapum aquifer by the thick sedimentary interbed of the Vantage Member of the Miocene Ellensburg Formation. The cities of Moscow and Pullman as well as the University of Idaho and Washington State University rely heavily on the Grande Ronde aquifer to supply their water needs. Across the Pacific Northwest, the CRBG contains important aquifers, many of which are in a state of decline, thus estimating recharge and uncertainties are broadly important to sustainable management of regional aquifers.

1.2 Objectives and Scope

Multiple studies have been conducted that estimate recharge in the Palouse Basin. The estimates vary widely and most have no bounds of uncertainty associated with them. This study focuses on determining the uncertainty in recharge to the Wanapum aquifer. Also, the interaction of social and scientific uncertainty and their coupled effect on decision

making is discussed in an interdisciplinary chapter. The specific objectives of this study are to:

1. Analyze historical water level and pumping data to calculate a recharge rate for the Wanapum aquifer and an associated estimate of uncertainty,
2. Use Bayesian Model Averaging and expert elicitation to combine previous estimates of recharge and determine an aggregate recharge rate and corresponding level of uncertainty for the Wanapum aquifer, and
3. Assess the interaction between scientific uncertainty and social uncertainty, and their coupled effect on the decision making process.

Chapter II

Literature Review

2.0 Recharge Estimation Methods

Recharge estimation can generally be classified into physical, tracer, or numerical modeling approaches. Scanlon (et al., 2002) compiled a comprehensive review of these methods. This section is a summary of Scanlon (et al., 2002) for the purpose of providing the necessary background to understand this work, and the reader is referred to Scanlon (et al., 2002) for additional detail.

The water budget, or mass balance equation is the basis for many of the different methods and a simplified equation applicable to basins is shown in Equation 2-1.

$$P - Q_s - ET = R \tag{2-1}$$

P is the precipitation; Q_s is the surface water discharge out of the basin; ET is evapotranspiration; and R is the recharge. P, Q_s, and ET are measured or estimated and the residual is equal to the recharge, assuming that these are the only fluxes into and out of the basin and no change in storage. The accuracy of this method is dependent on the accuracy with which the different parameters are determined. Basin or watershed water budgets typically rely on one or more streamflow gauging stations, point measurements or spatial distributions of precipitation, and uniform or distributed calculations of ET from temperature and land use data.

Channel water budgets have been used to estimate surface water loss between gauging stations. Recharge calculated via channel water budget can be overestimated

because of bank storage, evapotranspiration, and perched aquifers or shallow water tables not connected to the main aquifer. The ground water table fluctuation method is based on a water budget of an aquifer, using the assumption that rises in ground water levels in unconfined aquifers are due to recharge. Pumping, entrapped air, and changes in atmospheric pressure may introduce error in the calculations and these components can be accounted for.

Seepage meters have been successfully used to measure seepage flux in lakes, streams, swamps, and tidewater areas at locations throughout the U.S. They provide only point estimates of flux and many measurements are necessary to determine a representative value of infiltration. Lysimeters are another physical technique that can be used to measure recharge. They are however expensive to construct and maintain and are better suited for evaluation of evapotranspiration at specific locations.

Multiple tracer techniques exist for determination of recharge including: heat tracers, isotopic tracers, applied tracers, historical tracers and environmental tracers. Diurnal or annual temperature fluctuations' can be used with inverse modeling software to estimate hydraulic conductivity. Recharge rates can be estimated from hydraulic head measurements coupled with the hydraulic conductivity. Isotopic tracers such as oxygen and hydrogen can provide information on recharge sources, but quantification of actual recharge rates is very difficult. Bromide, ^{3}H, and organic dyes are chemical tracers that when applied at the soil surface or in the soil profile can be used to estimate recharge rates. Sampling is done via test holes or trenching months or years after application, and the vertical distribution of the tracers is used to determine the velocity and recharge. Historical tracers are a result of human activity such as nuclear testing or contaminant spills and have been used to estimate

recharge rates over the past 50 years, and provide qualitative evidence of recharge. However, due to the uncertainties in concentration, source location and behavior of contaminants, quantifying rates of recharge is problematic and difficult. Chloride is an environmental tracer that is produced naturally in the earth's atmosphere and can be used to estimate recharge rates. Chloride concentration is inversely related to drainage in the unsaturated zone pore water, and this relationship results in more accurate estimation of recharge at low drainage rates. Chloride mass balance has been widely used and is useful to estimate recharge rates up to 300 mm/year.

Darcy's law can be used to estimate recharge, and while this method is easy to apply, it requires information on large scale effective hydraulic conductivity and hydraulic gradient. Estimates are often highly uncertain due to variability in hydraulic conductivity. This is especially true with unsaturated hydraulic conductivity where values vary over orders of magnitude based on moisture content.

Numerical modeling has proven a useful tool for estimation of groundwater recharge. Ground water flow models are developed based on hydrologic data and calibrated to reproduce historical trends. Uncertainties in hydraulic conductivities directly affect recharge estimation and may result in non unique solutions as long as the ratio of recharge to hydraulic head is constant.

2.1 Palouse Basin Recharge Investigations

Palouse water resource investigations were initiated in 1897 by I. C. Russell. He conducted a water supply reconnaissance of southeastern Washington which included the

Palouse and its artesian wells (Russell, 1897). Many investigations and reports have been completed since then regarding the geology, hydrogeology, aquifer properties, and recharge to the Grande Ronde and Wanapum aquifers. The geology and hydrogeology are discussed in depth by Foxworthy and Washburn (1963), Jones and Ross (1972), Barker (1979), and Bush (2005). Stevens (1960) and Foxworthy and Washburn (1963) used a rudimentary water budget analysis to estimate the recharge to the basalt aquifers through the loess. Single values for precipitation and evapotranspiration for the entire Basin were used in the water budget. Stevens indicated an error estimate of 25 % in his report. Fealko (2003) used a mass balance of the Paradise Creek watershed to probabilistically calculate the recharge to the Wanapum aquifer. Gauging stations were used to determine surface water run-off, and Parameter-elevation Regressions on Independent Slopes Model (PRISM) data were used to distribute precipitation spatially. PRISM data for temperature values was used in potential evapotranspiration calculations with Hargreaves method. Dungel (2007) built on Fealko's work and used Stella software to develop a systems model of the Palouse Basin. The hydrologic component of the model was based on a mass balance of the Palouse Basin. The Basin was divided into six different sub-basins and PRISM data were used to determine precipitation and evapotranspiration. Distributed actual ET was computed using the procedure of Thornthwaite and Mather. The model used data from several surface water gauging stations and output an estimate of recharge for the Wanapum and Grande Ronde aquifers.

Ground water flow models have also been used to model the Palouse Basin and all the flow models estimated recharge as an input to the model. Barker (1979) used a two-

dimensional ground water flow model to analyze ground water levels in the basin. Recharge in the model was estimated as leakage through a confining layer above the Grande Ronde aquifer and determined using Darcy's law. Barker's (1979) two dimensional model predicted water elevations through the year 2000, but water levels predicted for 2000 were observed in 1985, suggesting further work was necessary. A three-dimensional numerical ground water flow model was developed by Smoot and Ralston (1987) to help with management of the declining aquifer system. The model included a Grande Ronde basalt layer, a Wanapum basalt layer, and a surficial loess layer. Recharge to the upper layer of the model was estimated using a daily deep percolation model developed by Bauer and Vaccaro (1990). The model developed by Bauer and Vaccaro (1990) was based on mass balance and used daily time steps to estimate ground water recharge for both predevelopment and current land use conditions. An uncertainty analysis of the daily deep percolation model yielded an estimated uncertainty of 25%.

Radio carbon dating was used by Crosby and Chatters (1965) to analyze recharge to the basalt aquifers. They concluded that there was no measureable recharge in the Moscow area and that ground water was distinctly stratified with a well defined relationship between age and elevation. They collected most of their samples from the Wanapum formation and only four of the 50 samples came from the Grande Ronde formation. The results indicated that minimal recharge was occurring in the Pullman area and no recharge was detected in the Moscow area. Research by Baines (1992) contradicts Crosby and Chatters results and indicates recharge is occurring in the Moscow sub-basin. Further analysis using Carbon-14 dating was conducted by Douglas et al. (2007) with most samples analyzed coming from the

Grande Ronde basalts. Ages ranged from modern for the Wanapum aquifer to 26,400 years for the lower Grande Ronde and reflect the vertical travel times from land surface to the sampled location. Larson et al. (2000) analyzed ground water samples from the Grande Ronde and Wanapum aquifers for stable isotope ratios. Isotope ratios for the Wanapum and upper Grande Ronde aquifers showed an overlap with isotope ratios for the Palouse range indicating that recharge is occurring. Larson found that deep water in the lower Grande Ronde aquifer was not precipitated under current atmospheric conditions and recharge rates are substantially lower than were estimated previous to this study.

O'Brien et al. (1996) used chloride mass balance to estimate mean recharge fluxes and found that recharge varied depending on the topography. A similar analysis utilizing chloride mass balance was conducted by O'Geen (2004) which found that recharge rates vary across the basin and vertical percolation can be restricted by sequences of paleosol fragipans. Studies conducted by Johnson (1991) and Muniz (1991) investigated infiltration through the surficial loess using one-dimensional infiltration models to analyze the recharge. They found that recharge through the loess was dependant on the topography and likely influenced by macropores.

Baines (1992) used pumping data from Moscow well #2, Moscow well #3, UI well #1, and UI well #2 and water level data from a USGS observation well located northeast of the University of Idaho near Paradise creek to determine the sustained yield from the

Wanapum aquifer. Two different methods of analysis were employed by Baines to determine the sustained yield: the Hill method and the zero water level change method.

Badon (2007) conducted a series of four aquifer tests on Moscow city wells #2, #3, and #6 to determine aquifer properties as well as the extent of compartmentalization that exists in the Moscow area. The known extent of the cone of depression extends from the Bond well in the north to the Brandt well in the south, but the east and west bounds are not well defined indicating significant compartmentalization. Badon concluded that Moscow #2 and #3 weren't hydraulically connected in the short timeframe (72 hours) that the pump tests were conducted, but recent research has shown Moscow #2 and #3 to be connected on a longer monthly time scale (personal communication Dr. Jim Osiensky).

2.2 Bayesian Model Averaging

Methods of combining models' results to improve aggregate performance have been explored for the past 40 years, but little progress has been made until recently. New theoretical developments and computing power have enabled researchers to use more complex algorithms to implement Bayesian Model Averaging (Hoeting et al., 1999). BMA is a statistical approach for combining models which provides a description of the predictive uncertainty that accounts for between-model and within-model variances. The BMA procedure is described in more detail in the Methods section. BMA has been successfully applied in many different fields including statistics, management, science, medicine, meteorology, and hydrology (Duan et al., 2007). In hydrology, BMA has been applied to

stream hydrographs, ground water flow models, and recharge models. Duan et al. (2007) successfully applied BMA to stream flow predictions. Three different hydrologic models were used to generate a nine member ensemble of hydrologic predictions for three different watersheds. The three models were suited for capturing different aspects of the hydrograph: peak flow, mid-flow and low-flow. The results showed that the BMA scheme improved the predictive performance by accentuating the strengths of the different models in capturing different phases of the hydrograph. Ye et al. (2008) used BMA to evaluate recharge model uncertainty for the Death Valley regional flow system, which includes the Yucca Mountain nuclear repository. The prior probabilities for five different recharge models were determined using expert elicitation in a research laboratory environment. The prior probability is a subjective value which reflects experts' belief about the relative plausibility of a given model based on its agreement with existing data and information. Posterior model probabilities were calculated using model calibration data and the prior probabilities of the individual models. BMA yielded an estimate of posterior mean and variance of head and flux. The posterior variance of BMA was greater than the variance for any individual model because it also incorporated conceptual uncertainty (Ye et al., 2008). Nueman (2003) discusses a comprehensive strategy for hydrogeologic modeling and uncertainty analysis that incorporates Maximum Likelihood Bayesian Model Averaging (MLBMA). The strategy uses site characterization data and site monitoring data to obtain an optimal combination of both prior information and model outputs, and is essentially the same as BMA with the key difference being how the posterior probability is estimated. MLBMA provides an excellent avenue to combine the predictions of several competing models and analyze their predictive uncertainty.

2.3 Expert Elicitation of Prior Probabilities

The use of experts both formally and informally to assess the probabilities of given predictions has been used in fields ranging from nuclear waste regulation (DeWispelare et al., 1995) to hydrology (Ye et al., 2008) to ecology (O'Leary et al., 2008). Keeney and Winterfeldt (1991) and DeWispelare et al. (1995) outlined a methodology for eliciting probabilities from experts in complex technical problems. Ye et al. (2008) built on the work completed by Keeney and Winterfeldt (1991) to further define the methodology for expert elicitation of probabilities and suggested a seven step process for conducting an expert elicitation as follows.

Step 1: Identification and selection of elicitation issues

Three issues should be addressed when assessing model uncertainty. Is the set of methods used to determine recharge complete? What are the plausibility ranks of the models? What is the probability value that best represents the confidence you would place in a given model?

Step 2: Identification and selection of the experts

Three types of experts should be used in an expert elicitation: generalists, specialists, and normative experts. Generalists should have a broad understanding of the study goals and a good understanding of the technical aspects, while not necessarily being at the forefront of their field. Specialists should be at the forefront of their specialty, but may not have the broad understanding of the generalist. The normative expert would conduct the elicitation and have training in probability theory, psychology and decision analysis.

Step 3: Discussion and refinement of the issues

This step allows for the experts to discuss and refine the issues and quantities that will be elicited.

Step 4: Training for the elicitation

The purpose of the study, the elicitation issues, and the biases that may occur during the elicitation are addressed in this step.

Step 5: Elicitation

The experts are asked to fill out a questionnaire answering questions that progress from qualitative to quantitative with assignment of probabilities the last question

Step 6: Analysis, aggregation and resolution of disagreement

The expert's answers are analyzed and aggregated to yield a final probability estimate. A simple arithmetic mean as well as an iterative aggregation method is used to determine the mean.

Step 7: Documentation and communication

Steps one through six should be well documented to maintain the credibility and integrity of the elicitation (Ye et al., 2008) (Keeney and Winterfeldt 1991) (DeWispelare et al., 1995).

2.4 Uncertainty and Decision Making

Scientific uncertainty can play a significant role in the decision making process, thus it is important to quantify when possible. An overview of this subject is presented here with more depth presented in Chapter 5. A study conducted by Policansky (1998), found that many water resource problems are couched in scientific terms, while the real dispute was not

scientific in nature. In this work four case studies were analyzed and the findings were that clarifying the science helped, but the real issue in some cases was rooted in value judgments not science. It was found that scientific reports provided a basis for decision making even though there was uncertainty in the results. Decision makers should be made aware of uncertainties, but values, economics, and other considerations all play a part in the final decision. Scientific uncertainty should not be hidden or ignored, but addressed as a part of the decision making process. Uncertainty estimates can be used to improve risk assessment and provide a basis for informed decision making (Reckhow, 1994). Harrison (2007) experimented with a two- stage decision making process that used Bayesian programming to consider stochasticity, parameter and model uncertainties. The method was applied to illustrate a water quality management problem and used Bayesian programming to update uncertainty in each stage of a two stage adaptive management process. Uncertainty is inherent in the decision making process, but should not be an excuse for inaction or no management. Management schemes can address the uncertainty associated with various decision alternatives and make decisions based on the acceptable degree of uncertainty.

Chapter III

Methods

3.0 Recharge Estimation Using Historical Data

A recharge rate and associated estimate of uncertainty is determined from re-analysis of historic pumping and water level data for the Wanapum aquifer. The data used are pumping and water elevations measured in the Wanapum aquifer from 1965 to 1987. Water levels in the Wanapum aquifer declined 125 feet from 1895 to 1960 (Jones and Ross, 1972), but in the mid 1960s most of the pumping from the Wanapum aquifer by the City of Moscow and the University of Idaho was curtailed. During the period from 1965 to 1987 the pumping from the Wanapum aquifer was at a minimum and water levels recovered 36 feet by 1987. Baines (1992) used these data in his work, and the re-analysis is conducted with more recent information on well radius of influence.

Badon (2007) conducted a series of four aquifer tests on Moscow city wells #2, #3, and #6 to determine aquifer properties as well as the extent of compartmentalization that exists in the Moscow area. For each test, wells completed in the Wanapum and Grande Ronde basalts were observed to determine if a response to pumping could be identified. Moscow #2 is completed in Wanapum basalts and has an open interval from 2,328 to 2,532 feet above mean sea level. Two of the tests pumped from Moscow #2 for 24 hours 2 minutes and 74 hours and 27 minutes respectively. According to well logs referenced by Badon (2007), the open or screened portions the Appaloosa Horse Club well, Elks #5, UI #2 and Moscow #3 are consistent with the top and bottom of the Wanapum formation of

Moscow #2, but showed no response to pumping of Moscow #2. Moscow #3 is cased through the Wanapum basalts, but it is not clear from the well logs if the casing allows water from the Wanapum aquifer to enter the well or if it is grouted in place. Of the ten wells monitored for aquifer test # 2, the Bond and Brandt wells showed a definitive response to the pumping of Moscow #2. Aquifer tests #3 and #4 were conducted on Moscow #3 and Moscow #6 and none of the observation wells displayed a response to either of these tests. Additional research has indicated that Moscow #3 and Moscow #2 are not connected short term, but are connected at a longer time scale (personal communication, Dr. Jim Osiensky, 2009).

The aquifer tests indicate that the Wanapum aquifer system is poorly hydraulically connected and experiences significant compartmentalization. Aquifer tests #1 and #2 suggest lateral heterogeneity and anisotropy in the Wanapum aquifer system with transmissivity the highest in the north-south direction. The known extent of the cone of depression for Moscow #2 and Moscow #3 ranges from the Bond to the Brandt well and is elliptical in shape.

(GoogleEarth.com, 15 Feb. 2009)

Figure 2: Map showing the location of the USGS, Bond, Brandt, Moscow #2, and Moscow #3 wells

Pumping data from Moscow #2 and Moscow #3 from 1965 to 1987, water surface elevation from USGS observation well (39N 05W 07DDC1), and new information regarding

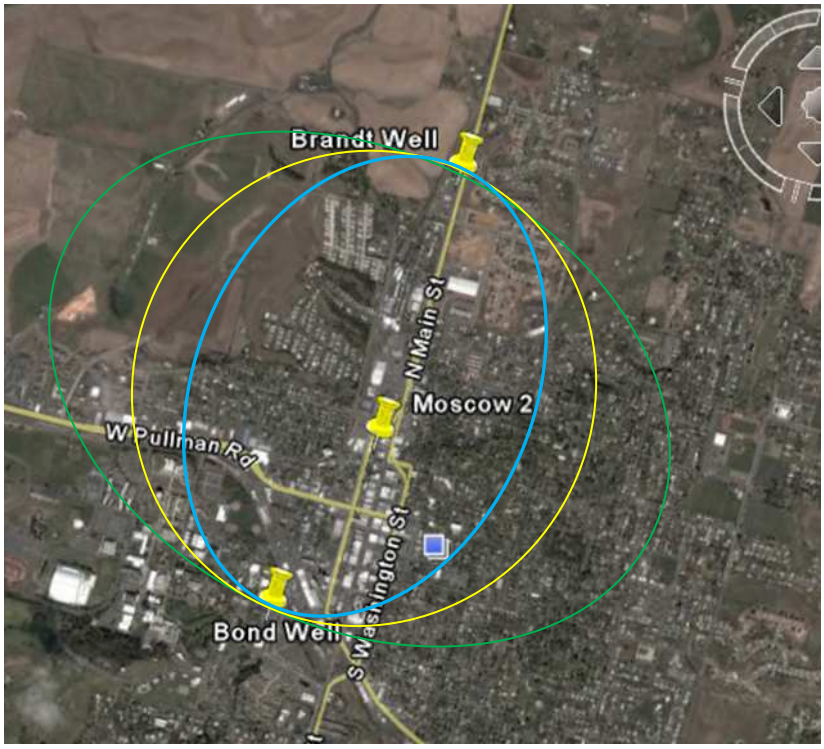
the extent of the cone of depression for Moscow #2 and #3 is used in this analysis. Water levels below land surface and pumping from Moscow #2 and #3 are shown in Table 1.

Table 1: Water level for USGS observation well (39N 05W 07DDC1) and pumping volumes for Moscow #2 and #3

Year	Water level, distance below land surface (feet)	Yearly pumping from Moscow #2 and #3 (millions of gallons)
1965	79.8	112.82
1966	72.8	40.36
1967	68.1	22.56
1968	66.5	40.25
1969	63.8	41.06
1970	60.7	2.02
1971	58.6	8.34
1972	57.0	0.00
1973	56.9	116.75
1974	56.7	95.26
1975	58.5	120.70
1976	55.8	180.13
1977	55.4	85.30
1978	55.1	148.21
1979	56.6	165.13
1980	55.7	165.02
1981	55.8	103.20
1982	53.3	121.04
1983	52.3	53.16
1984	51.1	34.31
1985	50.0	58.37
1986	48.6	18.09
1987	47.3	5.75

The USGS observation well (39N 05W 07DDC1) was monitored from 1937 to 1987 when an obstruction in the well made it impossible to take further measurements. The observation well is believed to have been outside of the influence of Moscow #2 and #3 during the recovery period of 1965 to 1987. If this assumption is correct, the water level measurements would be free from the influence of pumping. If the USGS well were subject to influence of pumping from Moscow #2 and #3, the measured change in water levels would be greater than the actual change in the system. The resulting affect would cause recharge rates to appear higher than they were.

The extent of the cone of depression described by Badon (2007) indicates that the cone of depression is elliptical in shape. Badon (2007) indicates that transmissivity is highest in the north-south direction because of lateral fractures acting as preferential pathways. The illustration of the cone of depression depicted in Badon (2007) shows an elliptical cone of depression with the long axis running east-west and the north-south boundaries at the Bond and Brandt wells. However, with transmissivity highest in the north-south direction, the cone of depression should be elliptical with the long axis running north-south from the Bond to the Brandt wells. For this analysis, three different areas are used to calculate the recharge: circular; elliptical, long axis running north-south; elliptical, long axis running east-west (Figure 3). The areas were calculated using distances measured with Google Earth.



(GoogleEarth.com, 15 Feb. 2009)

Figure 3: Cone of depression scenarios

Figure 3 shows the approximate areas of the different cone of depression scenarios: blue, small ellipse; green, large ellipse; yellow, circular.

Aquifer tests #1 and #2 conducted by Badon were used to estimate a range of storativity values for the Wanapum. The average of the storativity values is 0.04 and is used for this analysis. All the values for storativity fall within the expected range for an unconfined aquifer (0.01 to 0.3) suggesting that the Wanapum aquifer system is unconfined in the vicinity of Moscow #2 and #3(Freeze and Cherry, 1979).

The storage equation is used for this analysis and is presented below

$$\Delta S = I - O \tag{3-1}$$

The change in storage is equal to inflow minus the outflow

$$\Delta S = \Delta h * A * S \tag{3-2}$$

The change in storage is equal to the change in water level multiplied by the affected area (cone of depression) and the storativity. The recharge to the system is the inflow and outflow is assumed to be only pumping. Recharge is the net gain or loss to the aquifer and can be solved for directly.

$$Recharge = \Delta h * A * S + pumping \tag{3-3}$$

The recharge determined with this method is a combination of the total volume pumped plus the change in water level multiplied by the area of influence of the well and the storativity.

3.2 Expert Elicitation

In this work, the prior probabilities for the individual studies was elicited by having a set of experts assess the recharge estimates and the methods used to obtain them, as described in the Literature Review. The expert assigns a weight for each estimate. The prior probability obtained for each estimate is used to calculate a single weighted recharge estimate and variance.

Experts in the field of hydrology were contacted to determine if they would be willing to contribute their time for an elicitation process. The experts contacted were Dr.

Kent Keller, Dr. Mike Barber, Dr. Dale Ralston, Dr. Fritz Fiedler, Dr. Gary Johnson, Dr. Jan Boll, Dr. Tim Link, Dr. Paul McDaniel, Dr. Jerry Fairley, and Dr. Jim Osiensky, and Steve Robischon; they represented faculty from the University of Idaho, Washington State University, the Palouse Basin Aquifer Committee (PBAC), and a private consulting firm. Three of the experts are considered to be generalists and the remaining eight are specialists. The experts were given information on BMA, summaries and abstracts of the twelve studies considered, and a set of elicitation issues and questions. The elicitation addressed four issues:

- Is the set of methods used to determine recharge to the Wanapum aquifer complete?
- What are the plausibility ranks (1 to 12, least to most plausible) for each of the studies?
- What is the probability value that best represents the confidence you would place in each of the recharge studies?
- What value would you assign to the variance for each of the recharge studies?

Six general questions and five specific questions were asked to each expert. The questions are:

General Questions Regarding All Studies

1. Is the set of methods used to estimate recharge complete? (yes, no) If your answer is "no" specify additional plausible methods for recharge estimation.

2. Which study do you believe gives the best predictions of recharge?

3. What probability range (e.g., 40-60%) reflects the degree of belief that the study named in #2
   is the best?

4. Which study do you believe gives the worst predictions of recharge?

5. What probability range reflects your degree of belief that the study named in #4 is the worst?

6. What are the study ranks in terms of plausibility? Studies are ranked from 1 (least plausible) to 12 (most plausible). Different studies may have the same rank, indicating that the expert has the same degree of belief as to the plausibility of both studies.

Study Specific Questions

1. To what degree is the study based on solid physical principles? (high, intermediate or low)

2. Is the study contrary to any of your knowledge or experience? (yes, no) If "yes" please specify the reason.

3. Is the study qualitatively comparable to the others in terms of plausibility? (yes, no) If "no" please specify the reason.

4. What is the probability value that best represents the confidence you would place on this recharge study? Different studies may have the same rank, indicating that the expert has the same degree of belief as to the plausibility of both studies.

5. Given your knowledge of the method used, what variance, expressed in percent, would you expect from this method?

This elicitation closely followed the method recommended by Ye et al. (2008), with some variation in the recommended training period. A day long training period was recommended by Ye et al. (2008), but due to the time constraints involved, the experts were provided information on BMA and the recharge study summaries for them to review on their own. As discussed later, time was an issue for some experts even with requirements less than those recommended in the current literature.

The twelve studies included in the elicitation had recharge estimates that ranged from 0.2 (in/yr) to 4.8 (in/yr). The method and estimate of recharge for each study is shown in Table 2. More detailed summaries are available in the Appendix.

Table 2: Studies Included in the Expert Elicitation

Study	Method	Estimate of Recharge (in/yr)
Stevens (1960)	Mass balance	1.2
Foxworthy and Washburn(1963)	Mass balance	0.9
Barker (1979)	Darcy's Law	0.94
Smoot and Ralston (1987)	USGS Daily Deep Percolation Model	3.6
Bauer and Vaccaro (1990)	USGS Daily Deep Percolation Model	2.8
Johnson (1991)	One dimensional infiltration model (LEACHM)	4.2
Muniz (1991)	One dimensional infiltration model (LEACHM)	2.1
Baines (1992)	Hill method and zero change method	1.06
O'Brien (1996)	Chloride mass balance	0.98
O'Geen (2004)	Chloride mass balance	0.17
Dungel (2007)	Mass balance	1.8
Reeves (2009)	Storage equation	4.8

3.2 Bayesian Model Averaging

Bayesian model averaging is used to combine recharge estimates based on their prior probabilities and determine an average recharge rate and corresponding degree of uncertainty. BMA is a statistical approach for combining models which provides a description of the uncertainty that accounts for between-model and within-model variances (Duan et al., 2007). Let recharge $\bar{R}$ be the quantity to be forecast and $M = [M_1, M_2, \ldots, M_k]$ the set of all models considered, and D is the set of observation data. The probability density function of the BMA probabilistic prediction of y can be represented by

$$p(\bar{R}|D) = \sum_{k=1}^{K} p(M_k|R) \cdot p_k(\bar{R}|M_k, D) \tag{3-4}$$

where $p_k(\bar{R}|M_k, D)$ is the posterior probability of model prediction M_k being correct given the observation data, D, also known as the likelihood of model M_k being correct. K is the number of models considered. The posterior probabilities add up to one, $\sum_{k=1}^{K} p(M_k|D) = 1$, and they can be viewed as weights on individual models. The posterior probabilities are obtained using site observations and the prior probabilities.

$$p(M_k|R) \approx \frac{\exp\left(-\frac{1}{2}KIC_k\right)p(M_k)}{\sum_{l=1}^{K}\exp\left(-\frac{1}{2}KIC_l\right)p(M_l)} \tag{3-5}$$

The posterior probability is $p(M_k|R)$; KIC is the Kayshap information criterion which uses calibration data, number of parameters, and a weight matrix and sensitivity matrix; $p(M_k)$ is the prior probability of M_k (Ye et al., 2008). The posterior probability is the prior probability conditioned on observation data from the different models. The studies that have been examined for this analysis do not provide the luxury of reams of observation data and more discussion on the Kayshap criterion is neither necessary nor applicable because the

prior probabilities are used in place of the posterior probabilities. The posterior probability is the prior probability conditioned by observation data. The prior probabilities are subjective values, whereas the posterior probability is a modification of the subjective value based on a given models consistency with available data (Ye et al., 2008). Modifying the priors on the observation data reduces the uncertainty associated with a given probability estimate. Using the priors in place of the posteriors will mean that the uncertainty estimate is conservative. For example, the estimate for uncertainty using prior probability may be 60%, but if more information were available to modify the prior probability the uncertainty might be reduced to 50%.

The Bayesian estimate of the mean and variance of $\bar{R}$ is given by,

$$E[\bar{R}|D] = \sum_{k=1}^{K} E[\bar{R}|D,M_k]\, p(M_k\,|D) \tag{3-6}$$

$$\begin{aligned} Var[\bar{R}|D] = {} & \sum_{k=1}^{K} Var[\bar{R}|D,M_k]\, p(M_k\,|D) \\ & + \sum_{k=1}^{K} (E[\bar{R}|D,M_k] - E[\bar{R}|D])^2 p(M_k\,|D) \end{aligned} \tag{3-7}$$

$E[\bar{R}|D]$ is the mean and $Var[\bar{R}|D]$ is the variance of $\bar{R}$ under model M_k because of the uncertainty associated with model M_k.

In essence the BMA prediction is the average output of the individual model weighted by the likelihood that the individual model output is correct given observation data D (Duan

et al., 2007; Raferty et al., 2003). The variance of the BMA prediction is a measure of the uncertainty that accounts for both between-model variance and within-model variance.

Chapter IV

Results

4.0 Recharge Estimation Using Historical Data

A five year moving average of both water level change and pumping was used to determine recharge using equation 3-3. The results are shown in Table 3.

Table 3: Five year moving averages of water level, pumping, and recharge

Year	Water level, distance below land surface (feet	Change in water level (feet)	Five year moving average of change in water level	Yearly pumping from Moscow #2 and #3 (millions of gallons)	Five year moving average of pumping from Moscow #2 and #3 (ft^3)	Recharge, circular cone of depression (in/yr)	Recharge, small ellipsoid cone of depression (in/yr)	Recharge, large ellipsoid cone of depression (in/yr)
1964	83.9							
1965	79.8	4.06		112.82				
1966	72.8	7.06		40.36				
1967	68.1	4.63	4.02	22.56	6888886	4.0	5.0	2.9
1968	66.5	1.66	3.83	40.25	3919559	3.0	3.6	2.4
1969	63.8	2.66	2.82	41.06	3061452	2.3	2.7	1.8
1970	60.7	3.14	2.23	2.02	2456831	1.8	2.2	1.4
1971	58.6	2.02	1.91	8.34	4506849	2.3	2.9	1.5
1972	57.0	1.65	1.42	0.00	5959355	2.5	3.4	1.5
1973	56.9	0.08	0.43	116.75	9139926	3.0	4.3	1.5
1974	56.7	0.23	0.57	95.26	13744032	4.5	6.5	2.2
1975	58.5	-1.85	0.31	120.70	16030179	5.0	7.4	2.4
1976	55.8	2.72	0.37	180.13	16873441	5.3	7.8	2.5
1977	55.4	0.37	0.02	85.30	18745957	5.7	8.4	2.6
1978	55.1	0.36	0.57	148.21	19933626	6.4	9.2	3.1
1979	56.6	-1.48	0.00	165.13	17871714	5.5	8.0	2.5
1980	55.7	0.90	0.42	165.02	18829492	5.9	8.7	2.8
1981	55.8	-0.13	0.55	103.20	16282179	5.2	7.6	2.5
1982	53.3	2.46	1.10	121.04	12776337	4.4	6.3	2.3
1983	52.3	1.02	1.13	53.16	9918064	3.6	5.0	1.9
1984	51.1	1.26	1.43	34.31	7637062	3.0	4.1	1.8
1985	50.0	1.05	1.21	58.37	4547236	2.0	2.6	1.2
1986	48.6	1.37	1.26	18.09	**Average recharge**	**4.0**	**5.6**	**2.1**
1987	47.3	1.34	1.25	5.75				

A five year moving average helps to reduce the effects of yearly variations in pumping and recharge. The estimates for recharge are presented in Table 4.

Table 4: Average recharge for the Wanapum aquifer system

Average recharge, circular cone of depression (in/yr)	Average recharge, small ellipsoid cone of depression (in/yr)	Average recharge, large ellipsoid cone of depression (in/yr)
4.0	5.6	2.1

The recharge rates vary from 2.1 in/yr to 5.6 in/yr highlighting the importance of conceptual uncertainty associated with this method. The range of recharge rates is a direct result of the variation of area in the size of the cone of depression. The cone of depression from Badon (2007) is elliptical in shape with the long axis running east-west which would be indicative of high east-west transmissivity. This shape is a result of the lack of data points in the vicinity of Moscow #2 and #3. The program used to generate the cone of depression interpolated between known points. The shape of the cone of depression is likely somewhere between the circle and the small ellipse, based on the pump tests done by Badon (2007) which indicate a high north-south transmissivity and an idealized circular cone of depression, an average of which yields a recharge rate of 4.8 (in/yr).

Recharge to the Wanapum may be directly controlled by the degree of compartmentalization which exists. Some compartments may experience high rates of recharge while other may receive little to no recharge due to preferential pathways and

geologic features. Preferential flow paths play a large role in defining the shape of the cone of depression. The high north-south transmissivity described by Badon (2007) is likely the result of lateral fractures which provide preferential flow paths for both recharge and pumping. The cone of depression intersects Paradise Creek which is a potential source of concentrated recharge in the vicinity of Moscow #2 and #3. If this were the case, Paradise Creek could act as a constant head boundary and very little drawdown would be experienced in that vicinity.

The volume of municipal water pumped by the City of Moscow has a five percent error associated with it. The flow meters used by the city are calibrated to within five percent and regularly maintained to ensure high accuracy (email communication with Tom Scallorn). Water level measurements for the USGS observation well were taken with either a steel or electronic tape. The error in these measurements at a maximum would be 0.1 ft (Nielsen and Nielsen, 2006). These sources of error pale in comparison to the conceptual uncertainty. At a minimum the uncertainty would be five percent with a maximum of fifty-six percent based on the ratio of the large ellipse cone of depression scenarios to the average area of the circular and small elliptical cone of depression.

The average recharge in the vicinity of Moscow #2 and #3 determined by this analysis is 97 million gallons per year. The use of Moscow #2 and #3 as a municipal supply ramped up in 1991 and averaged 203 million gallons per year through 2005, by comparison the period from 1967 to 1990 averaged 72 million gallons per year. Approximately two thirds of the

water pumped from the Wanapum aquifer system is from Moscow #2 with the remainder from Moscow #3. Since pumping ramped up in 1991, there has been a slight decline of water levels in Wanapum aquifer system, indicating that pumping exceeds recharge and the current rate of pumping is not sustainable long term.

4.1 Expert Elicitation

Eight experts participated in this study, and individual expert names are not associated with their responses herein. The elicitations were conducted via personal interview over a period of two weeks. A meeting was set up with each expert and the elicitation was conducted in one to two hours depending on the depth of discussion for each of the individual studies, and the results documented on a questionnaire during the personal interview. The methods and issues regarding each study were discussed and the expert answered the general and study specific questions. The prior probability estimates for each individual study were aggregated using an arithmetic mean. An arithmetic mean was used because other iterative methods of aggregation are more time intensive, and the experts volunteering their time had a limited amount available for this exercise. Iterative methods also give very similar results to the arithmetic mean. Ye et al. (2008) used an iterative aggregation method that required the experts to place averaging weights on their own judgments as well as the other expert's judgments. Upon learning the other expert's assessments, expert *A* could change his probability estimate. The process would eventually converge on a single probability estimate for a given study. Ye et al. (2008) found that the difference in aggregating model probabilities using an arithmetic mean versus an iterative

method was only one percentage point for two of the five studies. The three remaining studies had the same probability regardless of the aggregation method.

The experts chose which study they felt was the best and the worst, and estimated the prior probabilities and the variance of the twelve studies based on their experience in hydrology and their knowledge of the basin. Figure 4 shows the range of prior probabilities for the individual studies.

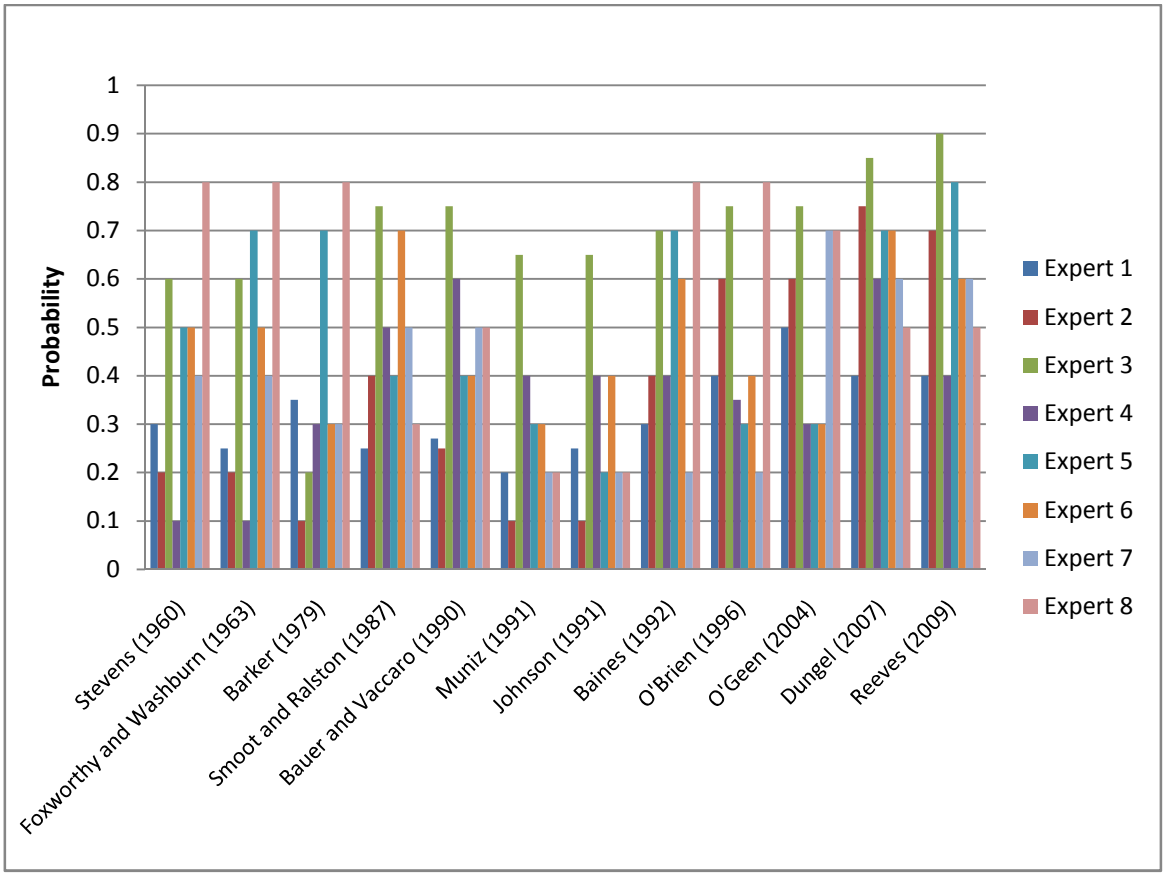


Figure 4: Prior probability distribution of recharge studies

The figure shows the prior probability estimated by each expert for each of the studies considered. This prior probability represents the expert's confidence that the study estimates a reasonable recharge rate. The prior probability estimated by the experts for Stevens (1960)

varied from 0.1 to 0.8. Similarly, the prior probabilities can be seen to vary for each of the individual studies. Johnson (1991) and Muniz (1991) have the lowest prior probabilities which vary from 0.1 to 0.65. These two vadose zone studies were conducted near Pullman, WA and were consistently ranked as giving the worst predictions of recharge for the Wanapum aquifer system. Several experts reasoned that the vadose zone studies estimate recharge to the loess, but because of lateral flow paths they do not give an accurate measure of the recharge reaching the Wanapum aquifer system. There is also significant heterogeneity in the Basin, and assuming soil properties are consistent between Moscow, ID and Pulllman, WA is likely incorrect. The two studies with the highest prior probability distributions are Dungel (2007) and Reeves (2009) which vary from 0.4 to 0.85 and 0.4 to 0.9. Reeves (2009) and Bauer and Vaccaro (1990) were ranked by the experts as giving the best predictions of recharge. The reasoning was that Reeves (2009) directly estimated recharge to the Wanapum aquifer system from historical water level and pumping data. The USGS was ranked high because of their reputation of high quality work and the effort put into addressing uncertainty through a sensitivity analysis. There was not the same consensus among the experts when ranking the best study as there was when ranking the worst study.

The aggregated prior probabilities for the individual studies can be seen below in Figure 5. The prior probabilities were aggregated using an arithmetic mean.

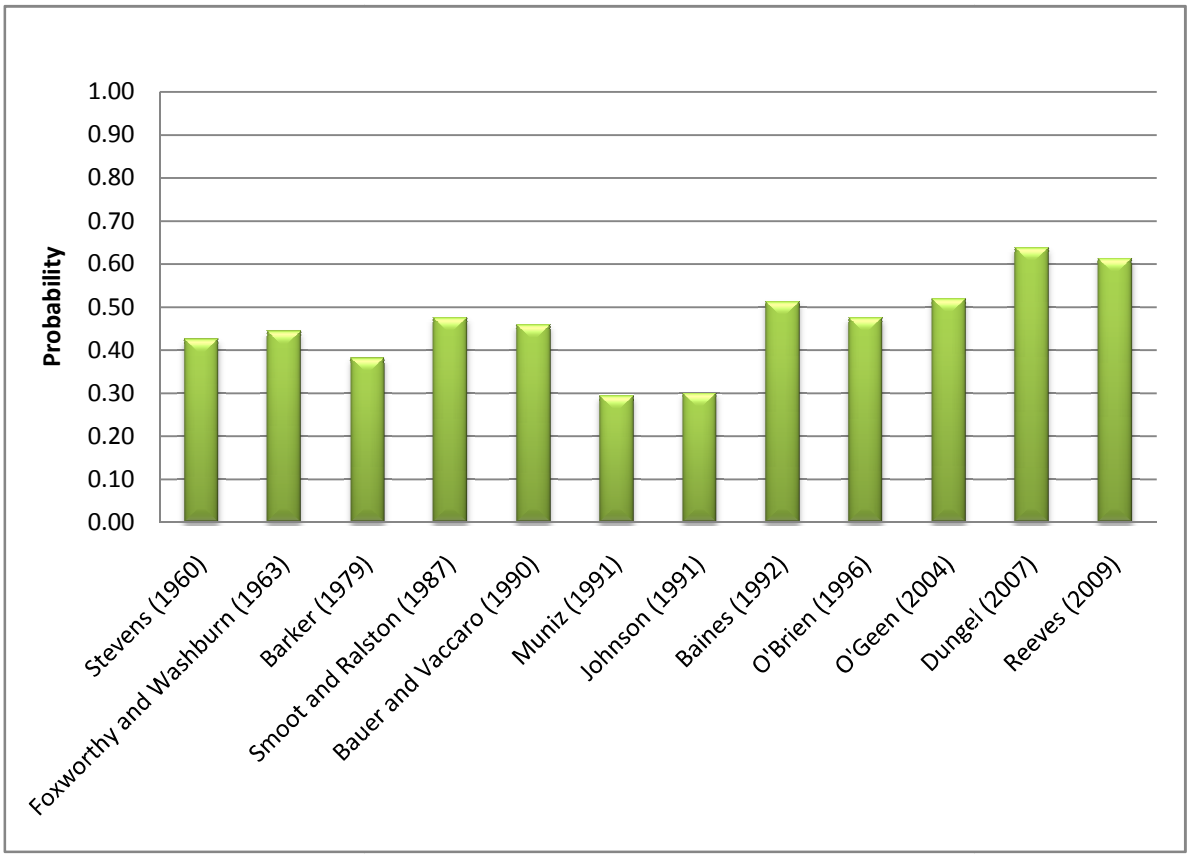


Figure 5: Aggregated prior probabilities of recharge studies

The graph shows the prior probabilities for the 12 studies varying from 0.29 to 0.64. Three observations are made based on figure 5. Johnson (1991) and Muniz (1991) have the lowest prior probabilities of 0.29 and 0.30. Stevens (1960), Foxworthy and Washburn (1963), Barker (1979), Smoot and Ralston (1987), Bauer and Vaccaro (1990), Baines (1992), O'Geen (1996), and O'Brien (2004) have prior probabilities varying from 0.38 to 0.52. The third observation is that two studies have higher prior probability, Dungel (2007) and Reeves (2009). They have probabilities of 0.64 and 0.61 which is 0.13 and 0.09 higher

than the next most likely study, O'Geen (2004). The spread in probabilities indicates the range of likelihoods of the studies. Experts also estimated the sample variance they would expect from a given method, because there was not enough existing data to quantitatively estimate the variance for the individual studies. Figure 6 shows the distribution of the variance.

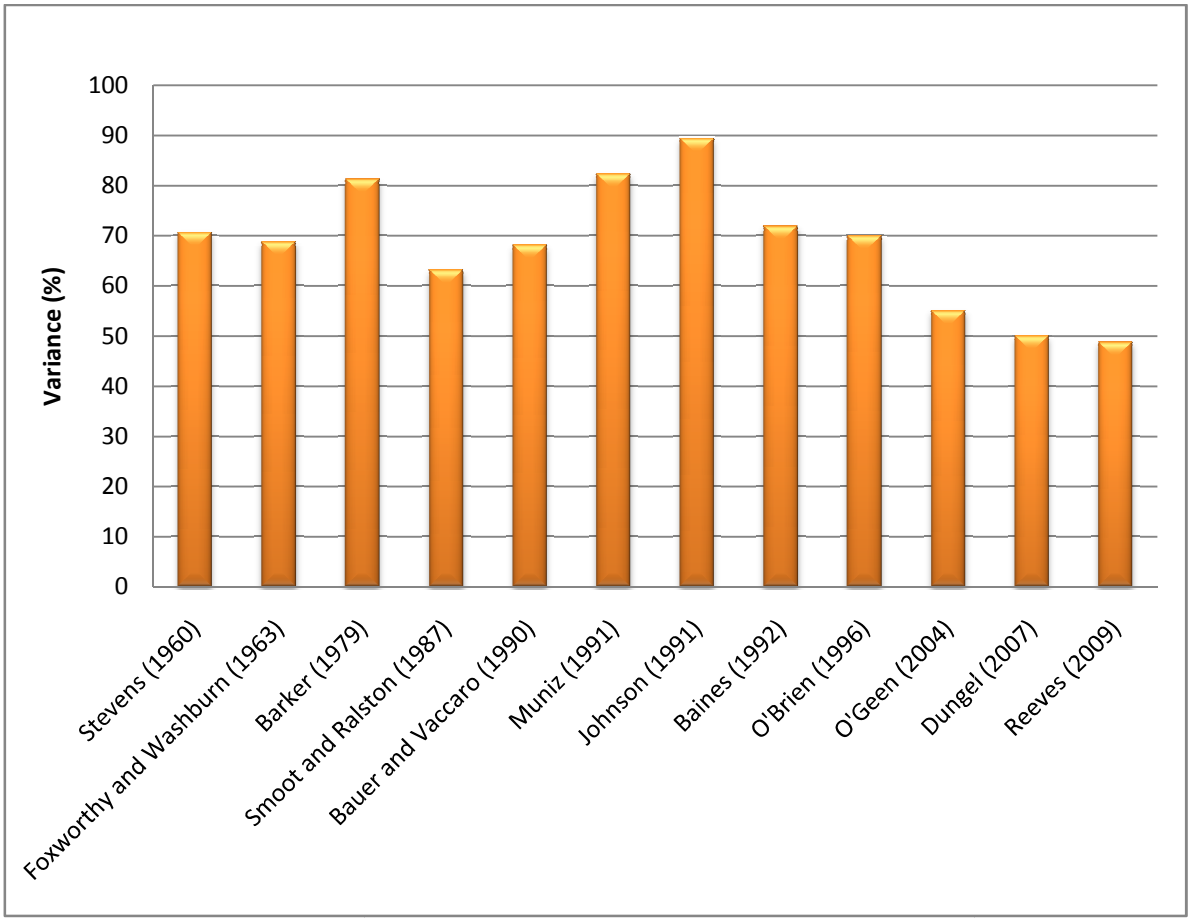


Figure 6: Aggregated variance of recharge studies

The variance for the individual studies ranged from 49 % to 89 %. The high range of variance indicates that a particular method will generate substantially different numbers when applied in different studies. The range in the variance indicates that the experts believed that the variance for some methods was less than others.

In conducting the elicitation interviews, several issues regarding time, scale, the definition of recharge, and applicability of the studies were brought up by the experts. All of the experts expressed that it was difficult to place probabilities on the individual studies and indicated that they could give better estimates if they had more time and resources to devote to the elicitation. At the time this work was conducted, most of the experts were full time faculty at the UI and WSU and had limits on the amount of time they could give to the elicitation. Recognizing that the experts were volunteering their time, the time requirements were kept at a minimum thought necessary to obtain useful data for BMA. It would not be feasible to expect the experts to give large amounts of their time to a project for which they are not funded to participate, neither could high participation be expected if the elicitation required a large time commitment. The elicitation interviews averaged around an hour in duration and the experts were given research material on the studies to review. The total time put into the elicitation varied from about an hour and a half to three hours depending on the expert. Several experts expressed concern about the time required, and two were reticent to provide elicitation data because of their concern for providing quality information with limited time.

The definition of recharge for this study had to be clarified during elicitation. Recharge for this study is defined as deep percolation that reaches the Wanapum aquifer system and would be available to the City of Moscow for municipal use. The experts expressed that the studies did not all specifically address recharge to the Wanapum aquifer system, and the recharge estimates in some of the studies may not pertain to the Wanapum aquifer system. For instance, Johnson (1991) and Muniz (1991) used a one dimensional analysis to estimate recharge through the loess; however, recharge to the loess may not be indicative of recharge to the Wanapum aquifer system because fragipans in the loess inhibit vertical infiltration and cause water to travel laterally. Scale was another issue brought up by many experts. The scale of the different studies varied from basin wide to specific locations. Investigations conducted by Reeves (2009), O'Geen (2004), Baines (1992), Johnson (1991), and Muniz (1991) were site specific, but studies by Dungel (2007), O'Brien (1996), Smoot and Ralston (1987), Bauer and Vaccaro (1990), Barker (1979), Foxworthy and Washburn (1963), and Stevens (1960) had implications basin wide. Estimations that are valid on a small scale may not be transferrable to a larger scale and vice versa. Estimates for hydraulic conductivity can vary significantly when going from small to large scale (Brooks and Boll, 2004).

The complexity of the studies was addressed by many of the experts. The general consensus was that the studies using the simplest approach to directly estimate the recharge were better than the more complex studies that didn't directly address recharge. The experts also indicated that the set of recharge methods was not complete and some type of tracer study should be conducted in the Basin.

4.2 Bayesian Model Averaging

The aggregated prior probabilities determined from the expert elicitation are weighted so that they sum to one and used in equation 3-6 and equation 3-7 to give the Bayesian estimate of the mean and variance. The weighted prior probabilities are shown in Figure 7.

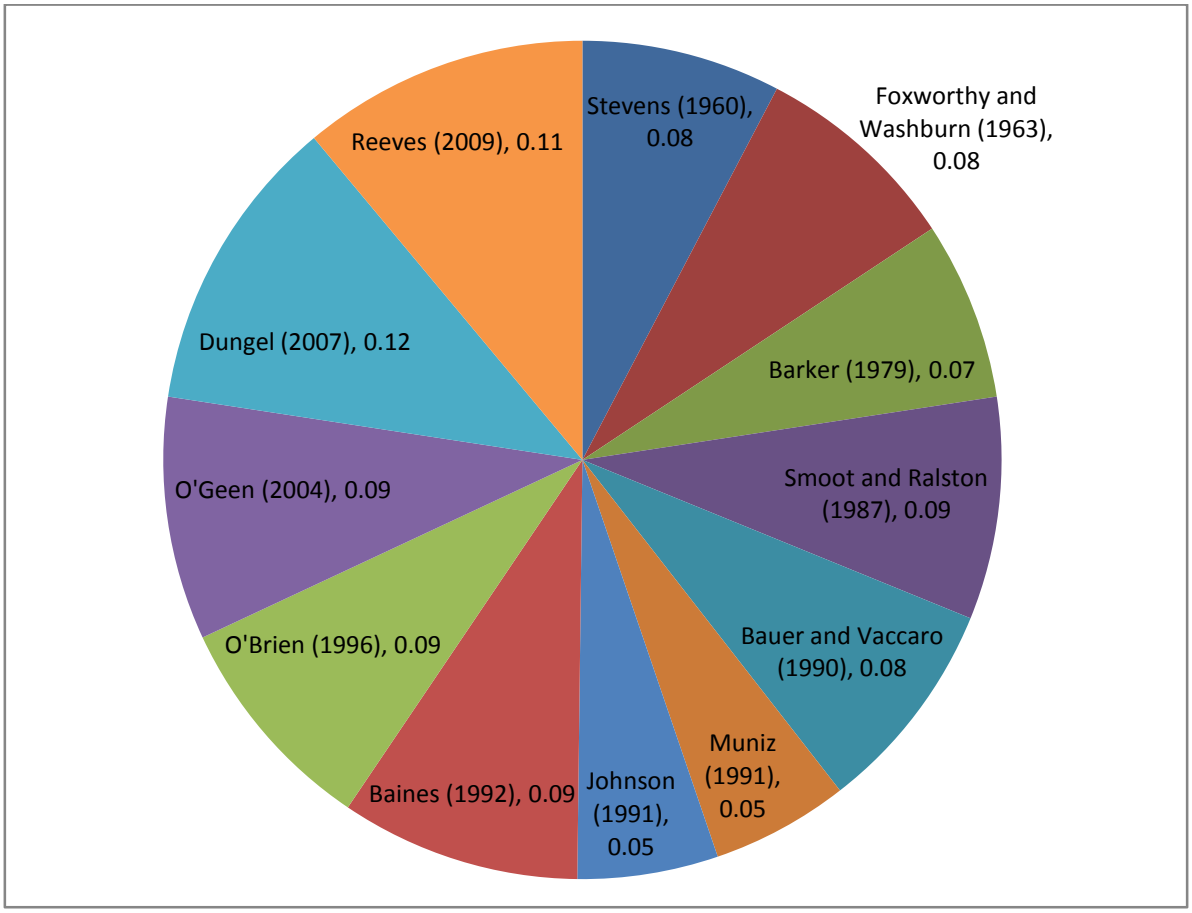


Figure 7: Weighted prior probabilities of individual studies

The weighted prior probabilities ranged from 0.05 for Johnson (1991) and Muniz (1991) to 0.12 for Dungel (2007). The prior probabilities are used to calculate both the BMA estimate and the variance. The variance takes into account both the within model

variance and the between model variance. Figure 8 shows the within and between model variance for each study.

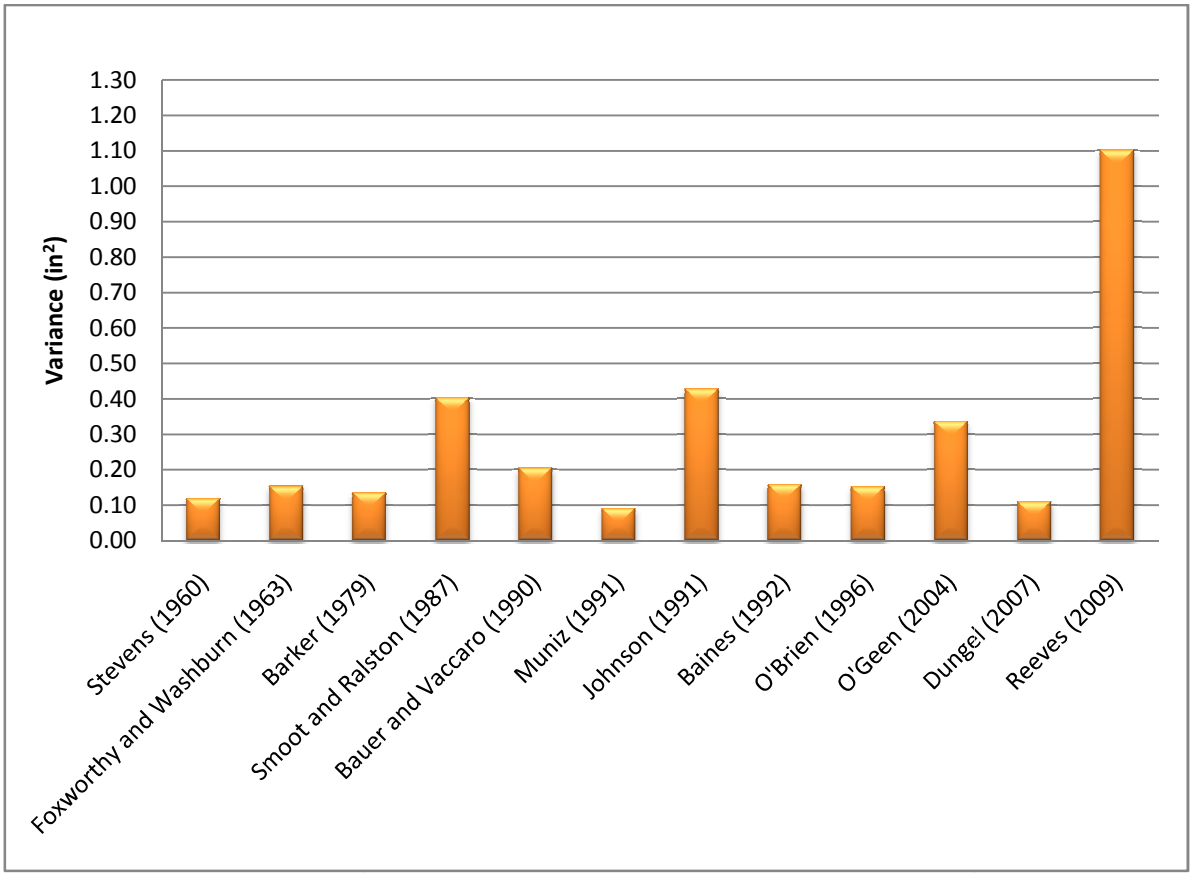


Figure 8: Variance within and between studies

The variance for each study is summed to determine the total variance, which is 3.4 in^2/yr^2. Reeves (2009) has the largest variance of all the studies. This is a result of the between model variance which adds the square of the difference between the BMA estimate and the individual study estimate. The average from Reeves (2009) is 4.8 in/yr and is based on assumptions about the cone of depression from Moscow #2 and #3. If the cone of depression is larger than assumed, the recharge volume would be distributed over a larger

area and would result in a smaller aerial estimate and a smaller variance. For example if the recharge were 3.0 in/yr the variance would be 2.6 in^2/yr^2 instead of 3.4 in^2/yr^2. This further highlights the importance of the conceptual assumptions in the method described previously.

The results of BMA are shown in Table 5, with different ways of quantitatively expressing uncertainty.

Table 5: Results of Bayesian Model Averaging

Bayesian Model Averaging results			
Recharge estimate (in/yr)	Variance $(in/yr)^2$	Standard Deviation (in/yr)	95% CI (in/yr)
2	3.4	1.8	2 ± 3.6

The estimate of recharge using BMA is 2.0 inches per year with a variance of 3.4 in^2/yr^2. The variance is the quantitative measure of uncertainty in this estimate and takes into account the variance within the individual studies as well as the variance between the studies (Duan et al., 2007). Most studies that do assess uncertainty only estimate the within model variance. Figure 9 shows the probability distribution of recharge with the standard deviation, variance and 95 % confidence interval, assuming a normal distribution.

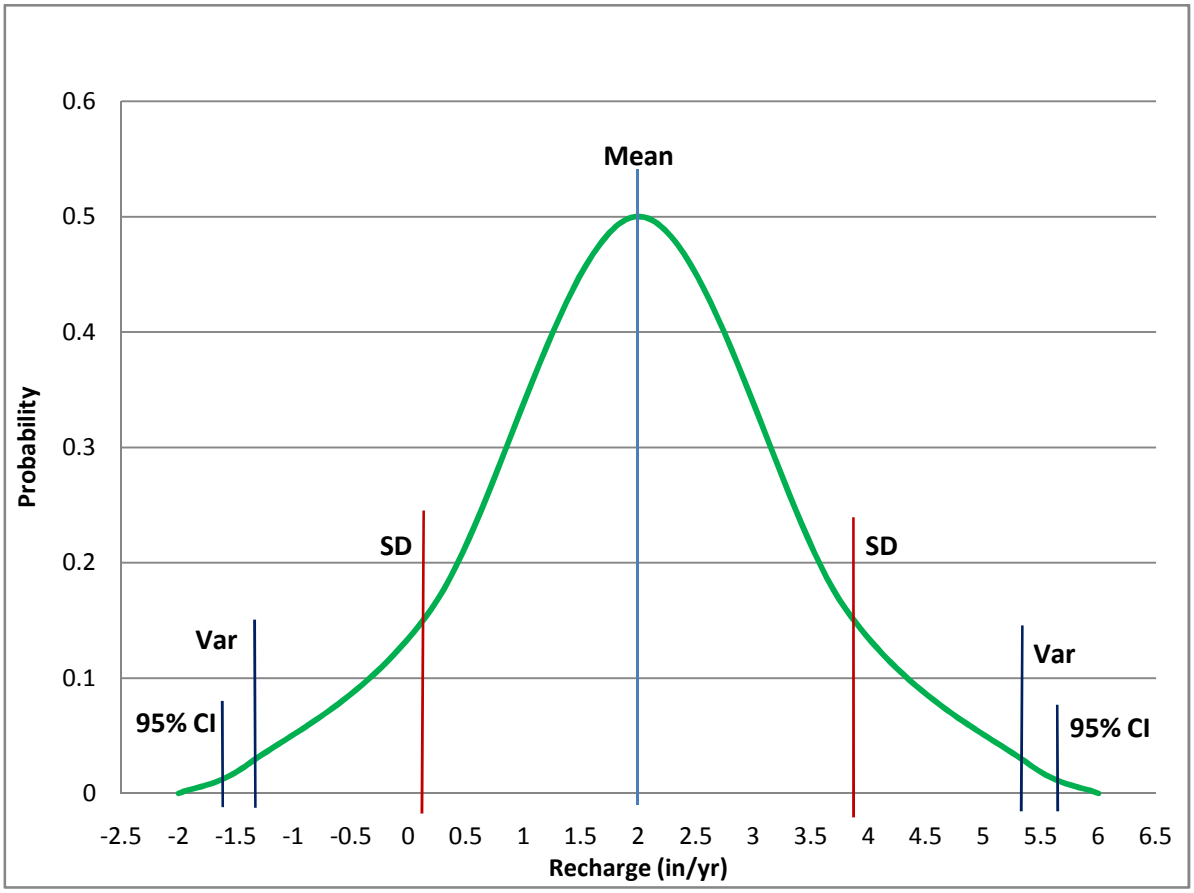


Figure 9: Probability distribution of recharge (not to scale)

Converting the variance to standard deviation, the recharge estimate would be 2.0 ± 1.8 inches per year. The 95 % confidence interval would be 2 ± 3.6 inches per year. As is typical (Ye et al., 2008), it is assumed in the analysis that the data are normally distributed. However, the physical lower bound for recharge is zero thus recharge is not rigorously normally distributed.

The estimate of uncertainty here is higher than seen in individual studies because it additionally incorporates the between study variance. The recharge estimate was derived

using studies that estimated recharged aerially as well as by total volume. All of the recharge numbers were converted to aerial estimates for use in BMA. The estimate of recharge determined with BMA is applicable over the recharge area of the Wanapum in the Moscow sub-basin. A volume of recharge could be determined once the recharge area has been delineated.

This research differs from the expert elicitation studies discussed in the literature in that the models to estimate recharge in the Palouse Basin were not available to generate data or new scenarios. The studies discussed in the literature review had available several models to generate output data used to condition the prior probabilities. The situation in the Palouse Basin represents a situation where observation data and model output data are more limited, but conclusions and results must be drawn despite limited data.

Chapter V

Social and Scientific Uncertainty and Implications on Decision Making

5.0 Scientific and Social Uncertainty

Physical and social sciences, though very different, complement each other. A broader understanding of water resource management within the Palouse Basin is facilitated when both physical and social science are concurrently considered. One uniting theme in both the physical and social scientific research on the Palouse Basin is uncertainty, which is a factor affecting decision making. In order to satisfy the interdisciplinary requirement of the Water Resource Program this chapter is co-author this chapter with Katherine Bilodeau, another Master's candidate in the Water Resources Program whose research focused on social uncertainty in the Palouse Basin. Minor differences are a result of different graduate committees. The following co-authored chapter addresses the following question: *What are uncertainties of the social and physical systems of a water resource and how might these combined variables affect decision making in the Palouse Basin?*

In the physical hydrologic system, uncertainty is present as parameter uncertainty and conceptual uncertainty. Parameter uncertainty is the mathematical error that would result from calculating a hydrologic parameter such as streamflow, precipitation, or other parameters in the water budget. Conceptual uncertainty results because the actual hydrogeologic structure, stratigraphy and bounds of an aquifer system cannot be perfectly represented nor even understood. In the social sciences that focus on the Palouse Basin, uncertainty can have multiple inferences. Uncertainty can simply be that the stakeholders'

knowledge, perceptions, beliefs, and opinions are unknown. Response behavior of individuals is another social aspect of uncertainty.

5.1 Decision Making Approaches

Several approaches to decision making can be employed for natural resource management, and these approaches can rely on a combination of criteria on which to base decisions and system feedback. One important component of decision making is the identification of who has the authority to make the decision. When multiple decision making entities are involved, jurisdiction is a boundary to the subsequent decision making strategy (Holecheck et al, 2003). Federal agencies, such as the U.S. Environmental Protection Agency and the U.S. Fish and Wildlife are not bound by geographical jurisdiction but by purpose, i.e. protection of environmental components. On the other hand, state, county, and municipal agencies are limited by their political jurisdiction. The overlap of political and environmental jurisdictions in regards to a natural resource obviously complicates and limits decision-making processes.

The first approach for decision makers is the ever-present option to do nothing, or to maintain the status quo. If the status quo is maintained, users do not change behavior in resource use or allocation. No change in resource use means nothing new is risked, nothing new is gained, and nothing new is lost. However, choosing to "do nothing" does not mean a decision has not been made. Maintaining status quo regarding resource use is a passive decision to continue using the resource without change, which may have adverse effects. If, for example, the status quo is resource *harvest* (a take of the resource faster than the physical

system's ability to recharge the resource), then a decision to "do nothing" will ultimately result in complete resource depletion.

The alternative to the passive decision to "do nothing" is to make an active decision using one of several criteria and approaches. Social order in a natural resource use follows a balance of three basic criteria identified by Firey (1960): what is ecologically possible, what is socially acceptable, and what is economically feasible. Loomis (2002) added two criteria to Firey's essential criteria: 1) operational practicality; and 2) distributional equity among the current population/between present and future generations. Although not every criterion needs to be addressed with a natural resource decision, sustainable management of a particular natural resource use will balance all of the criteria (Firey, 1960; Loomis, 2002).

Past management or decision making approaches have relied simply on historical trends or what has worked using the best current information at the time of the decision (Montgomery, 1995; Johnson, 1999). These decision making approaches suggest that decision making is a one-time event that may have a permanently altered effect on the situation. Although a decision can permanently alter a situation and have unintended consequences, decision making in the face of a natural resources dilemma is not necessarily a one-time occurrence, more developed approaches reflect that of management reactions to previous decisions in a continual manner. Decision making can be a process of feedbacks and successive decisions referred to as "monitor and modify" (Johnson, 1999). "Monitor and modify" uses decision feedback to gain knowledge (or reduce uncertainty) about a variable and adapts with subsequent decisions that reflect the increased knowledge of the system.

In the 1970s, this "monitor and modify" evolved to what is now known as *adaptive management* (Holling, 1978). Although this new type of management has been applied to different ecosystems and the resulting management classified under other names, i.e. watershed analysis (Montgomery et al., 1995)), the philosophies and principles have fundamentally identical components, which enables the classification of this approach into one specific category. Adaptive management functions on the premise that, although a system may not be understood with absolute certainty, the process of involving stakeholders and responding to the constant feedback of new knowledge will enable better overall understanding and benefit the guidance of further decisions (Montgomery 1995; Lee, 1999; Johnson, 1999). A guiding philosophy in this management paradigm integrates social and biological needs from the beginning in order to support decision making processes and lead to an increased likelihood of successful management implementation (Montgomery, 1995). In essence, adaptive management further develops monitor-and-modify management with an interdisciplinary approach; various stakeholder epistemologies come together, gaps in the comprehensive knowledge are identified and become scientific questions, and management adapts to the new knowledge found, incorporating it into future decision-making processes (Holling, 1978; Lee, 1999; Montgomery, 1995; Johnson, 1999; POST, 2004; Kemmis, 2002).

The temporal decision to act "now" or "later" has become a component of decision-making that may have notable effects. The resolve to wait for more or better information and then make a decision (i.e. to decide "later") is a strategy based on the concept of the Precautionary Principle (PP). In its purest theoretical form, the PP requires evidence that the proposed risk-taking decision will not *adversely* alter the present situation (Gollier and

Treich, 2003). However, this is not to suggest that absolute conclusive evidence is necessary to make a decision involving risk; the premise of the PP looks at the intersection between the cost of waiting to make a decision, and the gain of better information for a presumably less risky decision at a later date.

The physical and social scientific factors unique to every resource management scenario can contribute to which approach or combination of approaches are used. Multiple decision making entities with overlapping jurisdictions may affect the priorities of the criteria and affect processes within those approaches. These factors undoubtedly include the particular nature of the social and physical uncertainties of each system.

5.2 Physical and Social Scientific Factors Affecting Decision Making Approaches

The science used to inform decision-making related to water resource problems can take various forms, such as streamflow hydrographs, well observation data, pumping data, flood exceedence probability, and hydrogeologic models. Depending on the complexity of the problem, the science to inform the decision makers may require that measured data such as streamflow or ground water elevations be incorporated into a model of the system. The challenge of modeling is to understand how the system works and reduce the uncertainty associated with model output. Reducing the uncertainty provides decision makers with better information when making a decision that involves legal, social, and scientific complexities. The decision to act based on scientific information can be reduced to a single parameter, uncertainty. Reducing the uncertainty in the physical system may necessitate action due to legal or social constraints.

Social factors that generally affect decision-making include what groups know about the resource, whether groups involved with resource harvest are willing to cooperate; the level of uncertainty involved in the system; and the social or political response to a management decision.

Natural resource management scenarios can sometimes be classified as a *social dilemma.* A social dilemma is the junction between unsustainable use and the self-interest vs. collective interest of the resource users was. It was initially described by biologist Garett Hardin in his article *The Tragedy of the Commons* (1968), and further developed by Dawes in 1980 (Biel and Garling, 1995; Roch and Samuelson, 1997). Dawes (1980) established two defining characteristics for a social dilemma: (1) the social payoff is higher to users who choose not to cooperate and harvest according to their self-interest, in other words, users who *defect*; and (2) the collective payoff of users who unanimously choose to act in the collective interest, or to *cooperate*, is higher than if all users defect. The preference to act individualistically or to cooperate is a *social value orientation* (Messick and McClintock, 1968). This orientation, formed by the willingness of individuals or groups to cooperate, can dictate which decision-making strategy is employed, as an approach such as adaptive management is not conducive to defecting individuals/groups.

Value orientations affect decision-making in terms of harvest and uncertainty as well. Experimental research has consistently identified that resource users who cooperate (act in the collective interest), harvest at a significantly lesser rate than their defecting counterparts (Roch and Samuelson, 1997; Kramer et al., 1986; Liebrand, 1984; Loomis et al., 1995). Roch and Samuelson (1997) found that in resource scenarios of higher

uncertainty groups or individuals acting in the collective interest maintained or decreased their harvests while defectors tended to increase harvest rate.

Another social factor that affects decision-making is the public or political response to a decision. When the political or social responses are the first concern, it is not uncommon for a decision to be to "do nothing" (Johnson, 1999). The PP may further feed into politics affecting the approach by losing focus of the true issue or using system uncertainty to postpone a decision pending further information (POST, 2004).

5.3 Uncertainty and Decision Making

Decision making can take place under any level of uncertainty. Understanding the level of uncertainty and the range of decision alternatives available is more likely to contribute to effective decision making than attempting to narrow uncertainty in the science or the decision alternatives (Pielke and Conant, 2003). Scientists and decision makers often mean different things when they seek to "reduce uncertainty". Scientists may be seeking to reduce the uncertainty in the understanding of a complex system while the decision maker is seeking to reduce uncertainty in the decision outcomes (Pielke and Conant, 2003). When scientists seek to inform decision makers of new science it is vitally important for them to be on the same page when they are attempting to reduce uncertainty. Both the scientist and decision maker must understand that uncertainty does not prevent decision making, but gives a basis for choosing between several alternatives and determining if additional data is are needed (Reckhow, 1994).

5.4 Palouse Basin

True to water resource management everywhere, the political overlay of the hydrogeology in the Palouse Basin is distinct and unique. The basin underlies several cities and is encompassed primarily by two counties, Latah County in Idaho and Whitman County in Washington (Larson et al., 2000). Water management is governed separately by each state with federal government considerations. In Idaho, the Idaho Department of Water Resources (IDWR) manages Idaho surface and groundwater (IDWR, 2008). The state water agency in Washington is the Department of Ecology (Washington Department of Ecology, 2008). As discussed earlier, authority is an integral component to decision making, and the overlapping jurisdictions of water management in the Palouse (i.e. the state authorities and municipal authorities) complicate water resource management in the Palouse Basin on a fundamental level.

Falling ground water levels have been an issue in the Palouse Basin for the last fifty years. The first response to address falling ground water levels in the Moscow sub-basin was to drill deeper wells and bypass the shallower Wanapum aquifer. Water levels in the deeper Grande Ronde aquifer system have decreased at a fairly constant rate since it was first developed in the late 1800s. In recognizing the need for both research and education of the public and policy makers about Palouse Basin water resources, the Pullman-Moscow Water Resources Committee (currently known as the Palouse Basin Aquifer Committee, or PBAC) published the Ground Water Management Plan (1992). This document established PBAC as an organization that plays a role in water resource management, develops a water resource management plan, conducts and promotes studies of ground water resources, and encourages public involvement in plan development through educational programs and

forums. However, it is important to note that PBAC has no decision-making authority, and wording carefully reflects such in the expressly stated role of the Pullman-Moscow Water Resources Committee:

> *The role of the COMMITTEE is to encourage ENTITIES to implement the PLAN. The COMMITTEE will also monitor the success of the ENTITIES in carrying out their action plans and achieving the goals of the PLAN. Each ENTITY will be expected to adopt an action plan, interfacing with the stated goals of the PLAN. The COMMITTEE will provide guidance related to water-use plans, conservation strategies relative to water use, implementation policies, and the preparation of local ordinances or zoning regulations (PMWRC, 1992)*

In the Ground Water Management Plan, PMWRC (1992) also established the goal of limiting aquifer pumping increases to one percent per year with changes in pumping rates implemented by agreement of the cities of Moscow (ID) and Pullman (WA), the counties if Whitman (WA) and Latah (ID), and the Universities of Idaho and Washington State. This decision essentially maintained the status quo because growth in the basin has been one percent per year.

Management decisions in the Palouse Basin likely have been constrained by several factors. The scientific information about the Palouse Basin aquifers has been developed incrementally over a period fifty years. Incremental changes in new science may not motivate decision makers to change how they make decisions (Morss et al., 2005). Additionally, decision makers are constrained by time, money, and resources and may be constrained by federal, state, and local regulations from using new information. Such constraints reduce decision maker's motivation to learn to use new methods and scientific information. A disconnect between the recommendations by PBAC and the decision making process currently exists (personal communication Fritz Fiedler, 2009). The role of

PBAC is to guide decisions, however, if PBAC representatives are not fully facilitating two-way communication between their organizations and the PBAC, the disconnect likely will result in hindering or stalling the decision making process. Decision makers seeking new scientific information often turn to scientists whom they trust and with whom they have a long-term relationship with (Morss et al., 2005). To aid in the decision making process, the studies that PBAC commissions must not just give general scientific knowledge to the decision makers, but must generate data or information that applies to the decision at hand. When the needs of the decision makers are clearly understood, then the studies conducted can directly address those needs, both reducing uncertainty in the science and educating the decision makers in the process. Finally, significant scientific and social uncertainty, including the risk-taking that uncertainty creates in decision-making, have likely contributed to slower changes with Palouse Basin aquifer management.

Uncertainty in the physical system has been an issue for decision makers in the Palouse Basin. For example, in the Palouse Basin the primary source of municipal water is the Grande Ronde aquifer system. Water level records show a steady decline of 1.5 to 2 feet per year for the last several decades. It is uncertain if the Grand Ronde aquifer is receiving recharge, and if the pumping is in excess of the recharge. If the mining of groundwater was 100% certain from a scientific perspective, then the decision to curtail or continue pumping would be based on the legality of ground water mining (I.C. s 42-237a). The Wanapum aquifer system receives recharge, but there is no consensus on the amount of recharge. Estimates of recharge in the Basin range from 0.2 to 4.8 inches per year. Part of this thesis addressed this issue by taking twelve studies that estimate recharge and using an expert elicitation process to determine the probability that each recharge estimate is correct.

Bayesian Model Averaging (BMA) was used to combine the recharge estimates and determine the mean and variance. The BMA estimate by Reeves (2009) helps to resolve the uncertainty in recharge to the Wanapum aquifer by taking into account the conceptual and parameter uncertainty, in a manner not done by previous estimates. Recharge was estimated at 2.0 ± 1.8 inches per year, and this estimate provides a measure to analyze the Wanapum aquifer system for sustainability and can be adapted as new information becomes available. The expert elicitation process was very useful because it showed a consensus between experts regarding the studies of recharge to the Wanapum aquifer system, and yielded an estimate of uncertainty. It also highlighted the need to better understand the recharge area and recharge mechanisms of the Wanapum aquifer.

A considerable amount of social uncertainty exists in the Palouse Basin as well. Approximately 44 percent of residents surveyed in the Palouse Basin did not know the origin of their household water, suggesting a need for outreach educating the public about their water source (Bilodeau, 2009). Survey respondents also self-rated their awareness of water-related organizations and knowledge about decision-making processes low. This could potentially make decision-making riskier because public response to decisions would subsequently present a higher degree of uncertainty. The public indicated a low knowledge about water resource planning/decision-making that occurs in the basin, and the proportions are alike between well owner and municipal water user groups. Well owners and municipal water users have a moderately high concern for water resources on the Palouse, and perceive some problems with the water planning/decision-making within the community. Most importantly, 75 percent of survey respondents indicated interest in learning more. Although public response to specific measures cannot be gleaned from some general results the survey

produced, the combination of an apparent need for education outreach, interest in learning more, and perception of problems with decision-making create an environment where the public might successfully help scientists and policy-makers in the decision-making process.

5.4 Summary

This chapter examined scientific uncertainty in social and physical disciplines, and their coupled effects on decision-making. Uncertainty in the physical system affects our understanding of recharge to the aquifer systems, and physical system uncertainty can delay management decisions. Public perception, values, and responses to water resource management decisions might influence policy-makers. Without physical certainty guiding management decisions, and the public response unknown, decision-makers have incentive to adopt a Precautionary Principle strategy. Waiting for more information, given the uncertainty in physical and social science, is perhaps the least risky decision-alternative in terms of physical system alteration and social response. However, there is a fine line between waiting for more information and the decision to maintain the status-quo ("do nothing"). An alternative that reduces the risk that maintaining the status quo assumes is the implementation of conservation measures. Conservation of the resource will not adversely affect the system and would serve as an interim measure while efforts are made to reduce the social and physical uncertainty. Conservation could have economic impacts if conservation measures curtailed economic growth in the region. These impacts must be weighed when making a decision. Uncertainty does not (nor should not) completely prevent decision making. Early involvement of scientists, managers, decision makers, and the public in the decision making process enhances a comprehensive understanding of the

physical and social science components involved with the natural resource. It also gives decision makers and managers the opportunities to gather the specific information they would require to make an informed decision. The decision making approach best encompassing the characteristics described above is adaptive management. Decision makers could make the pro-active decision to conserve while waiting for better social and physical science. New information could be input into the adaptive management scheme in which physical science and social science complement each other in the decision making process by bringing comprehensive understanding of complex natural resource management issues together and providing knowledge for decision makers to proceed with management decisions despite existing components of uncertainty.

Chapter VI

Conclusions and Recommendations

6.0 Conclusions

Bayesian Model Averaging appears to be a useful tool for recharge estimation. The data for recharge in the Palouse Basin is not exhaustive and comes from somewhat disparate sources, but through the use of BMA a combined estimate of recharge and the associated uncertainty were determined. The expert elicitation process that was part of the BMA would likely yield slightly better results if more time and resources were available for the experts to engage in the elicitation process. However, this constraint will frequently be encountered in real situations. Funding the experts for a portion of their time might be a way to enable them to free up additional time to spend on the elicitation. In addition to the quantitative benefits of the elicitation, there are qualitative benefits to be gained. The elicitation process helped to identify areas that need further research such as a tracer type study. It also identified which studies were most applicable for estimating recharge to the Wanapum aquifer as well as those that were not. While not yet known, the expert elicitation process may lend more credence to the BMA estimate and reduce controversy over which estimate is best.

The estimate of recharge to the Wanapum aquifer system determined through BMA was 2.0 ± 1.2 inches per year. This estimate takes into account the variance within the individual studies as well as the variance between the studies and represents the understanding and knowledge of professionals that are familiar with the Palouse Basin thus giving more credence to the estimate. Quantifying the uncertainty as has been done in this

study gives decision makers a baseline from which to work from. The uncertainty can be targeted for reduction or several decision alternatives could be developed based on the uncertainty. The uncertainty does not prevent decision making but it provides a basis for choosing between various alternatives. The management strategy best equipped to deal with uncertainty is adaptive management which involves scientists, managers, decision-makers, and the public. Adaptive management helps to bring a comprehensive understanding of complex natural resource management issues together and provides knowledge for decision-makers to proceed with management decisions despite existing components of uncertainty. The BMA method is well-suited to adaptive management frameworks.

6.1 Recommendations for Additional Research

The experts identified a tracer study as being another valuable tool to address recharge in the Palouse Basin. A tracer study would utilize injected tracers or human generated tracers such as caffeine or pharmaceuticals that would be discharged from the wastewater treatment plant. A tracer study could be used to identify possible recharge areas to the Wanapum aquifer as well as the recharge rate.

An expert elicitation process and BMA might be useful to apply to the Grande Ronde aquifer to quantify both the uncertainty and the recharge; however, less data are available for the Grande Ronde. A similar expert elicitation process for the Grande Ronde thus might better focus on conceptual recharge mechanisms rather than specific recharge

estimates. It would also help to identify areas that need further research as well as areas where there is a consensus among the experts.

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Appendix A

Elicitation Data

Experts	1	2	3	4	5	6	7	8		
Study	**Probability**								average probability	Weighted probability
Stevens (1960)	0.3	0.2	0.6	0.1	0.5	0.5	0.4	0.8	0.43	0.08
Foxworthy and Washburn (1963)	0.25	0.2	0.6	0.1	0.7	0.5	0.4	0.8	0.44	0.08
Barker (1979)	0.35	0.1	0.2	0.3	0.7	0.3	0.3	0.8	0.38	0.07
Smoot and Ralston (1987)	0.25	0.4	0.75	0.5	0.4	0.7	0.5	0.3	0.48	0.09
Bauer and Vaccaro (1990)	0.27	0.25	0.75	0.6	0.4	0.4	0.5	0.5	0.46	0.08
Muniz (1991)	0.2	0.1	0.65	0.4	0.3	0.3	0.2	0.2	0.29	0.05
Johnson (1991)	0.25	0.1	0.65	0.4	0.2	0.4	0.2	0.2	0.30	0.05
Baines (1992)	0.3	0.4	0.7	0.4	0.7	0.6	0.2	0.8	0.51	0.09
O'Brien (1996)	0.4	0.6	0.75	0.35	0.3	0.4	0.2	0.8	0.48	0.09
O'Geen (2004)	0.5	0.6	0.75	0.3	0.3	0.3	0.7	0.7	0.52	0.09
Dungel (2007)	0.4	0.75	0.85	0.6	0.7	0.7	0.6	0.5	0.64	0.12
Reeves (2009)	0.4	0.7	0.9	0.4	0.8	0.6	0.6	0.5	0.61	0.11

Experts	1	2	3	4	5	6	7	8				
Study	Variance								Average variance (%)	Within study variance (in/yr)^2	Between study variance	Sum of within and between study variance
Stevens (1960)	50	25	70	100	70	50	150	50	70.63	0.07	0.05	0.12
Foxworthy and Washburn (1963)	50	25	75	100	50	50	150	50	68.75	0.05	0.10	0.15
Barker (1979)	50	50	100	75	50	75	200	50	81.25	0.05	0.08	0.14
Smoot and Ralston (1987)	70	20	50	75	60	30	150	50	63.13	0.20	0.21	0.40
Bauer and Vaccaro (1990)	75	40	50	50	70	60	150	50	68.13	0.16	0.05	0.21
Muniz (1991)	75	50	33	60	60	80	200	100	82.25	0.09	0.00	0.09
Johnson (1991)	50	50	75	100	80	60	200	100	89.38	0.20	0.23	0.43
Baines (1992)	50	50	65	60	60	40	200	50	71.88	0.07	0.09	0.16
O'Brien (1996)	50	20	50	100	30	60	200	50	70.00	0.06	0.09	0.15
O'Geen (2004)	20	20	50	100	30	70	100	50	55.00	0.01	0.33	0.34
Dungel (2007)	50	15	50	50	50	35	100	50	50.00	0.11	0.00	0.11
Reeves (2009)	50	15	25	60	50	40	100	50	48.75	0.26	0.84	1.10

Experts	1	3	4	5	6	7	8	9
best study	O' Geen	Reeves	Bauer and Vaccaro	Baines	Bauer and Vaccaro	Dungel	Stevens, Fox&Wash	Reeves
worst study	Bauer and Vaccaro	Stevens, Washburn	Johnson, Muniz	Muniz	O'Geen	O'geen	Muniz, Johnson	O'Brien

Determining the Bayesian Model Averaging Estimate

$$Re_{est} := \begin{pmatrix} 1.2 \\ 0.9 \\ 0.94 \\ 3.6 \\ 2.8 \\ 2.1 \\ 4.1 \\ 1.06 \\ 1 \\ 0.17 \\ 1.85 \\ 4.8 \end{pmatrix}$$

Estimates of recharge from individual studies

$$Prior_{probability} := \begin{pmatrix} 0.08 \\ 0.08 \\ 0.07 \\ 0.09 \\ 0.08 \\ 0.05 \\ 0.05 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.12 \\ 0.11 \end{pmatrix}$$

$$i := 0, 1 .. 11$$

$$BMA_{est} := \sum_{i=0}^{11} \left(Re_{est_i} \cdot Prior_{probability_i} \right)$$

$$BMA_{est} = 2.0 \quad \frac{in}{yr}$$

Determining the BMA estimate for the variance

$$\text{Variance} := \begin{pmatrix} 71 \\ 69 \\ 81 \\ 63 \\ 68 \\ 82 \\ 89 \\ 72 \\ 70 \\ 55 \\ 50 \\ 49 \end{pmatrix}$$

Variance in percent for individual studies, the within study variance

$$BMA_{var} := \sum_{i=0}^{11} \left(\frac{\text{Variance}_i}{100} \cdot \text{Prior}_{\text{probability}_i} \cdot \text{Re}_{\text{est}_i} \right) + \sum_{i=0}^{11} \left[\left(2.04 - \text{Re}_{\text{est}_i} \right)^2 \cdot \text{Prior}_{\text{probability}_i} \right]$$

$$BMA_{var} = 3.4 \quad \left(\frac{in}{yr} \right)^2$$

$$\text{Standard}_{\text{deviation}} := \sqrt{BMA_{var}}$$

$$\text{Standard}_{\text{deviation}} = 1.8 \quad \frac{in}{yr}$$

95% Confidence interval = 1.96 Standard deviations

$$CI := \text{Standard}_{\text{deviation}} \cdot 1.96 \qquad CI = 3.6$$

95% Confidence interval = 2.0 +- 3.6 in/yr

Appendix B

Summaries of Studies that Estimate Recharge in the Palouse Basin

Ground-Water Problems in the Vicinity of Moscow, Latah County, Idaho

by P. R. Stevens, 1960

Stevens used a water budget to estimate the amount of water available for recharge in the basin. The estimate for recharge was 1.2 inches per years, but Stevens also noted that "The amount of precipitation on the basin, less runoff and evapotranspiration, that is apparently available for ground water recharge is 4,000 acre-feet. However, a quantity of 4,000 acre-feet is within the limits of error (25%) of the estimates of evapotranspiration."

Ground Water in the Pullman Area Whitman County, Washington

by B. L. Foxworthy and R. L. Washburn, 1963

This report looked at the groundwater resources of the Pullman area in Whitman County, Washington to determine whether the 1959 rate of groundwater pumping exceeded the perennial yield of the developed aquifers, and if it was feasible to develop additional aquifers or artificial recharge. A water balance of the area was used precipitation, evapotranspiration, surface runoff, and surface inflow to determine the recharge to the aquifers. Recharge was estimated to be less than 1 inch (2.54 cm) per year.

Computer Simulation and Geohydrology of a Basalt Aquifer System in the Pullman-Moscow Basin, Washington and Idaho

by R. A Barker, 1979

A two dimensional computer model was developed to simulate the hydrologic characteristics of the Grande Ronde aquifer system in the Pullman-Moscow basin. Recharge was modeled as vertical leakage through a confining layer and was estimated with Darcy's law and trial-and-error simulations. The average over the study area was 0.94 inch (2.4 cm) per year.

Hydrogeology and a Mathematical Ground-Water Flow Model in the Pullman-Moscow Region, Washington and Idaho

by John Leach Smoot and Dale R. Ralston, 1987

A three dimensional numerical ground water flow model was constructed to guide in the management of ground water levels in the Columbia River Basalts in the Pullman-Moscow area of Washington and Idaho. The model incorporated a Grande Ronde Basalt layer, a Wanapum basalt layer, and a surficial loess layer. A recharge rate of 3.6 inches (9.1 cm) per year was calculated using a daily deep percolation model developed by the U.S. Geological Survey. The recharge model was a water balance that used precipitation, temperature, streamflow, soils, land-use, and altitude data to compute transpiration, soil evaporation, snow accumulations, snowmelt, sublimation, and evaporation of intercepted moisture. Daily time steps were used to calculate deep percolation. The three dimensional model was calibrated using the time-average method and evaluated through a history match procedure. The model incorporates numerous assumptions and simplifications and model predictions are indicative only of general trends for the future.

Estimates of Ground-Water Recharge to the Columbia Plateau Regional Aquifer System, Washington, Oregon, and Idaho, for Predevelopment and Current Land Use Conditions

by H. H. Bauer and J. J. Vaccaro, 1990 USGS WRI Report 88-4108

Estimates of the time-averaged ground-water recharge to Columbia Plateau regional aquifer system were computed using a daily deep percolation model. The deep percolation model uses precipitation, temperature, streamflow, soils, land-use, and altitude data to compute transpiration, soil evaporation, snow accumulations, snowmelt, sublimation, and evaporation of intercepted moisture. Daily changes in soil moisture, plant interception, and snowpack were computed and deep percolation calculated when soil moisture exceeded field capacity. Recharge estimates were made for individual cells in 53 zones for predevelopment and current land use conditions. Recharge estimates for the Palouse region were 2.79 and 4.13 inches (7.1 and 10.5 cm) per year for current and predevelopment conditions, respectively. A sensitivity analysis of the model led the authors to estimate uncertainty at 25%.

Computer Modeling of Vadose Zone Groundwater Flux at a Hazardous Waste Site

M.S. Thesis by Herminio R. Muniz, 1991 WSU

Vadose zone soil samples were collected from five locations at the Washington State University hazardous waste sites and were analyzed to determine moisture content, bulk density, and grain size. The infiltration model LEACHM was used to estimate infiltration flux through the vadose zone using soil core data, climatic data, and estimated soil parameters. The average results of the simulations indicated a recharge rate of 5.5 cm (2.1 in) per year

Estimating Groundwater Recharge Beneath Different Slope Positions in the Palouse Formations Using a Numerical Unsaturated Flow Model

M.S. Thesis by George Edward Johnson, 1991 WSU

Soil cores were taken from crestslope, backslope, and toeslope positions in the Palouse Region of Eastern Washington. Measured and calculated soil hydraulic properties and climatic data were used as input to LEACHM, a numerical unsaturated flow model. Calculated soil properties yielded an average recharge estimate of 10.5 cm (4.1 in) per year. Measured soil properties produced unreasonable recharge estimates.

Determination of Sustained Yield for the Shallow Basalt Aquifer in the Moscow Area, Idaho

M.S. Thesis by C. A. Baines, 1992 UI

Sustained yield from the shallow basalt aquifer in the Moscow area is determined using two methods: the Hill method and the zero change method. A maximum estimate of sustained yield was 500 to 520 million gallons per year while maintaining a water level of 2479 ft. If distributed over a three mile radius of influence, it would be the equivalent of 1.06 in (2.7 cm) per year.

Multiple Tracers of Shallow Ground-Water Flow and Recharge in Hilly Loess

by R. O'Brien, C. K. Keller, and J. L. Smith, 1996

Vertical profiles of tritium and nitrate pore-water concentrations were determined to ~8 m depth across two loess hilllslopes, and mean recharge fluxes were estimated from chloride mass balance. Recharge fluxes were found to be 5-10 times larger at the mid- and toe- slope positions than at the top slope; recharge fluxes ranged from 0.3 – 3.0 cm/yr, with 2.5 cm (1 in) per year being the average for the mid- and toeslope positions. The recharge flux calculated using the chloride mass balance method is 2-10 times smaller than estimates based on other hydrologic methods. This discrepancy is possibly due to the fact that Cl-based recharge estimates do not include any flux contribution from preferential pathways.

Paleosols as Deep Regolith: Implications for Ground-water Recharge Across a Loessial Climosequence

by A. T. O'Geen, P. A. McDaniel, J. Boll, C. K. Keller, 2004

To assess water movement across the Palouse Basin, pore-water Cl^- and $\delta^{18}O$ distributions were measured to 6-m depths in three catchments representing a climosequence across the basin. Hydraulically active valley positions making up 10% of the study area did not yield reliable results due to seasonably high ground water tables and multiple perched water tables. Homogeneous deep regolith composed 37% of the study area and had a recharge rate of 10 mm per year. Heterogeneous deep regolith made up 33% of the study area and had recharge rates less than 3 mm per year. The weighted average of recharge for the study area was 0.43 cm (0.17 in) per year.

Water Resource Sustainability of the Palouse Region: A Systems Approach

M.S. Thesis by Ramesh Dungel, 2007 U of I

A systems dynamics approach evaluated the sustainability of water resources of the Palouse Region using demographic, hydrologic, geologic and economic modules. A hydraulically separated module was used to estimate recharge to the Wanapum and Grande Ronde using a water balance at land surface. The Palouse basin was broken down into six sub-basins and precipitation, surface runoff and evapotranspiration were used to calculate recharge for each sub-basin. The average recharge to the Wanapum from the six sub-basins was 4.7 cm (1.8 in) per year.

Estimation of Recharge to the Wanapum Aquifer

Draft report by Matthew Reeves, 2009 U of I

Water level and pumping data from the Wanapum aquifer system during the recovery period of 1965 to1987 was used to estimate recharge to the system. Aquifer pump tests conducted by Badon (2007) yielded storativity values for the Wanapum in the vicinity of Moscow well #2 and #3 indicated that significant compartmentalization exists in the system. The storage equation was used along with five year moving averages of pumping and water level changes to estimate a recharge 4.8 in (12.2 cm) per year.